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PROBABILISTIC FUZZY APPROACH TO EVALUATION OF LOGISTICS SERVICE EFFECTIVENESS

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Abstract
Logistics service providers offer a whole or partial logistics business service over a certain time period. Between such companies, the effectiveness of specific logistics services can vary. Logistics service providers seek the effective performance of logistics service. The purpose of this paper is to present a new approach for the evaluation of logistics service effectiveness, along with a specific computer system implementing the proposed approach – a sophisticated inference system, an extension of the Mamdani probabilistic fuzzy system. The paper presents specific knowledge concerning the relationships between effectiveness indicators in the form of fuzzy rules which contain marginal and conditional probabilities of fuzzy events. An inference diagram is also shown. A family of Yager's parameterized t-norms is proposed as inference operators. It facilitates the optimization of system parameters and enables flexible adjustment of the system to empirical data. A case study was used to illustrate the new approach for the evaluation of logistics service effectiveness. The approach is demonstrated on logistics services in a logistics company. We deem the analysis of a probabilistic fuzzy knowledge base to be useful for the evaluation of effectiveness of logistics services in a logistics company over a given time period.

Keywords
fuzzy expert systems, fuzzy hybrid systems, probabilistic fuzzy systems, probability of fuzzy event, logistics company, logistics service provider, logistics service, effectiveness.

Introduction

The development of logistics has forced entrepreneurs to change how they act and operate. The need for specialization and professional customer services in the field of logistics directly contributed to the rise of logistics service providers offering diverse service packages. The changes in supply chains are stimulated by the incentive to cut costs within companies and the associated tendency to focus on core competencies, and core business activity [1]. In consequence, specific transportation and logistics functions are outsourced to specialized logistics service providers. In practice, a company unable to meet its customers' demands, expects a wide range of services from such providers. These services include packing, loading and unloading of goods, transportation, customs clearance, crossing permits, parcel tracking, storage etc. Such services, also known as logistics services, are very specific. In order to carry out a logistics service, a logistics service provider must perform one or more logistics functions for their employer, based on a specific contract, and in accordance with its terms. Market observations show that both the nature of services and the relationship with the customer are undergoing change. From the provider's viewpoint, there is an ongoing shift from the transactional approach and from commissioning separate functions towards commissioning the management of integrated actions and complex supply chains [2–5].

The basic service on the logistics service market, arising out of the need for moving various goods from their collection point to their destination, is the transportation service [1, 2, 6, 7]. Freight forwarding services, consisting in organizing transportation process, insurance, preparing vital documentation, and customs clearance, also play a significant role on the logistics service market. Broadly speaking, a logistics service, apart from transportation and freight forwarding, involves terminal services, such as cross-docking, storage, completion, and refinement: branding, language localization, repacking, laminating, minor repairs, bundling into promotional kits etc. [1, 8–10].

Logistics services can vary in complexity, and can be carried out in short or long supply chains. Market observations indicate that logistics services become increasingly sophisticated, by far exceeding their traditional perception [1, 4–7]. They begin to resemble projects characterized by singularity, uniqueness, temporariness, limited budget, and, occasionally, innovativeness. The majority of commissions received by logistics service providers constitute separate and singular transportation-freight forwarding-logistics processes, which necessitate detailed analysis, planning, as well as appropriate management methods. Therefore, they are often treated as a specific type of projects, called logistics projects [5].

A logistics project should be construed as a planned set of interrelated tasks to be executed over a fixed period, limited by budget and time, which is carried out in order to improve the efficiency and effectiveness of product flows and of the associated information in companies, supply chains or spatial systems [9]. According to another definition a logistics project is a set of tasks characterized by a timeframe, costs and organization, the aim of which is to perform a singular and unique action that sets out to optimize a specific logistics process [11]. Logistics project is a non-routine set of task apart from other projects by time and cost, the purpose of which is to perform a singular and unique action that effects change to the logistics system of a company or a supply chain within which this company operates [12–16].

The challenges faced by logistics service providers require non-standard, unique actions, typical for projects of a specific scope, with constraints on time and resources. The effectiveness of managing such companies is essential from the point of view of business activity of the subjects involved, as well as the supply chains and networks. The effective performance of such projects is fundamental in the management of such companies, affecting their level of competitiveness and share in the logistics market.

The remainder of the paper is organized as follows: in the next sections the main problem is formulated and the research background is described. A new approach to the evaluation of logistics service effectiveness is presented. Additionally, we provide an example illustrating this approach, and describe a computer system that implements it. Results and concluding remarks are presented in the final section of the paper.

Problem statement

The following problem can be formulated. Given is a logistics service provider. Over a certain time period such a company provides logistics services as integrated actions for complex supply chains. The logistics service is carried out with defined level of effectiveness. The considered problem comes down to answering the following question: how should we measure and evaluate the effectiveness of carrying out logistics services in a given logistics company? In order to solve this problem, we need to seek computationally efficient methods for measuring and effectively evaluating the performance of a given logistics service. This paper is devoted to coming up with an objective method of measuring logistics service effectiveness, taking into account the uncertainties of analyzed indicators, and permitting a qualitative-quantitative assessment of effectiveness using financial and non-financial measures.

Research background

In the literature, different interpretations, criteria and measurable quantities are associated with the term ‘effectiveness’. Effectiveness is a coefficient calculated based on the analysis of the relationship between the total costs and the effects they yielded. The diversity of possible effects engenders various forms of effectiveness. Economic effectiveness is considered most often. In theory and practice, different methods are employed in order to evaluate effectiveness. One can measure and evaluate the effectiveness of a company, department, logistics system, commission, project, a logistics service, etc. Depending on when effectiveness was evaluated, in the field of logistics services, we distinguish *ex-ante* evaluation (before the service is performed), an *ongoing* evaluation (while the service is being performed), and an *ex-post* evaluation (after the logistics service was performed). Carrying out a potential service necessitates evaluating effectiveness in the planning phase, as well as at the final stage. In order to calculate effectiveness *ex-ante*, appropriate measures need to be chosen and suitable methods must be used for evaluation, before a decision whether or not to provide a given logistics service is made. The aim of *ex-post* evaluation of logistics service effectiveness is to measure and evaluate the actual effects in order to compare them against the expected ones [1, 15–17].

The application of methods for the evaluation of the effectiveness of carrying out logistics services requires solving the problems of using the principles of economic calculus, according to which the costs and effects must be measurable and expressed in the same units; at the same time, a suitable selection criterion must be specified. This is difficult to achieve in practice. Not all effects, nor costs, are measurable, even though their impact on the final result can be significant. It is necessary to employ an appropriate tool for the evaluation of the effectiveness of logistics services. A performance measurement system (PMS) is one such tool. In the literature, it is defined as a set of measures used to quantify effectiveness and efficiency of actions [18]. A correctly designed and functioning performance measurement system for logistics services should indicate the factors crucial for achieving the goals of a given logistics service. Such a system should be based on both financial and non-financial indicators [15–17].

This paper presents a new approach to the evaluation of the effectiveness of logistics services, whereby we propose to employ a dedicated system, which allows to carry out not only measurements, but also a fuzzy probabilistic analysis of the effectiveness. In the framework of this system, the rules of the model represent knowledge in the qualitative and quantitative forms, i.e. describe it linguistically, and quantitatively as probabilities of selected fuzzy events. The assumed notation of rules allows to adjust the model to expert knowledge and empirical data, while facilitating simple analysis of knowledge directly recorded in the rules. The Mamdani probabilistic fuzzy model is the most often used model that allows to describe uncertainty in fuzzy and stochastic terms simultaneously [19, 20]. In addition, the system presented in this paper uses the conditional probability of fuzzy events from the conclusion to describe how logistics services are carried out in a selected logistics company. Such an approach permits a more accurate description of uncertainty in the evaluation of effectiveness. Concurrently, the application of parameterized triangular norms facilitates adjusting the inference operators to the analyzed problem.

The performance of the proposed approach is illustrated on the example of a real-life company, TransSL, providing specific logistics services. TransSL is a professional third-party logistics (3PL) provider which provides other companies with logistics services.

Research method

Qualitative-quantitative approach to knowledge representation

The concept of a probabilistic fuzzy knowledge base, which describes the relations between effectiveness indicators, is based on a knowledge representation methodology with the qualitativequantitative approach. The qualitative representation of knowledge is made possible owing to the application of fuzzy logic theory [21] and linguistic description of the variables under study. Then, every variable x can be expressed verbally with a value (linguistic term) $L(x)$, which is associated with a fuzzy set A. In the theory of fuzzy sets, the values from the universe of variables are members of fuzzy sets, taking into account the grade of membership expressed as a function $\mu_A(x)$, so that:

$$\mu_A : x \to \langle 0, 1\rangle, \qquad (1)$$

where 0 – signifies lack of membership of the value x in the fuzzy set A, 1– signifies full membership of the value x in the fuzzy set A, value between 0 and 1 signifies partial membership of the value x in the fuzzy set A.

A quantitative approach is concerned with the method of determining a probability measure $P(A)$ for the occurrence of a fuzzy event, i.e. the fuzzy set A defined in the space $\Re^n$, the membership function of which is measurable in the sense of Borel [22]. The probability measure is determined classically, i.e. numerically, as a number from the interval $\langle 0,\ 1\rangle$. The values of the measure result from the following relation:

$$P(A) = \sum_{i=1}^{n} \left[p(x^i) \cdot \mu_A(x^i)\right], \qquad (2)$$

for a discrete universe of discourse $\aleph = \{x^1, x^2, \ ..., x^n\}$, where $p(x^i) \in \langle 0,\ 1\rangle$ constitutes the (non-fuzzy) probability of the elementary event x^i, and $\sum_{i=1}^{n} p(x^i) = 1$.

If the elementary events $x^i \in \aleph$ are equally probable, the probability of a fuzzy event A in $\aleph$ is:

$$P(A) = \frac{Power(A)}{Power(\aleph)} = \frac{\sum_{i=1}^{n} \mu_A(x^i)}{n}. \qquad (3)$$

In practice, this relation is used to calculate the probability measure in a probabilistic fuzzy knowledge base.

The distinctive form of IF-THEN conditional rules enables a simple representation of the qualitative-quantitative approach to the description of the problem. A MISO (Multiple Input Single Output) system with N inputs and one output, contains a knowledge base in the form of conditional file rules. The first file rule of the knowledge base can be represented as follows [23–25]:

$$\begin{aligned}
\text{R1: IF } & x_1 \text{ IS } A_1^1 \text{ AND ... AND } x_N \text{ IS } A_1^N\ [w_1]\\
& \text{THEN } y \text{ IS } B_{1/1}\ [w_{1/1}]\\
& \ldots\\
& \text{THEN } y \text{ IS } B_{j/1}\ [w_{j/1}]\\
& \ldots\\
& \text{THEN } y \text{ IS } B_{J/1}\ \ [w_{J/1}]
\end{aligned} \tag{4}$$

where x_n – the n-th input variable of the model, $x_n \in \aleph_n \subset R$, $n = 1, ..., N$, y – output variable of the model, $y \in \Im \subset R$, A_1^n – linguistic value (fuzzy set) of the n-th input value in the first file rule, $n = 1, ..., N$, $B_{j/1}$ – linguistic value (fuzzy set) of output variable in the j-th elementary rule of the first file rule, $j = 1, \ldots, J$, w_1 – weight of the first file rule, which constitutes the probability of simultaneous occurrence of events from the antecedent of the rule $P(A_1^1 \times \ldots \times A_1^N)$, $w_{j/1}$ – weight of the elementary rule, which constitutes the conditional probability $P(B_{j/1}/A_1^1 \times ... \times A_1^N)$.

Construction of a knowledge base: descriptive versus prescriptive approach

A usual construction of a system with a probabilistic fuzzy knowledge base constitutes the *descriptive* approach [26]. A mathematical model for the control system (object or process) is not required. However, we require information about the linguistic description of variables and definitions of membership in fuzzy sets, which must be taken into account if we want to obtain 'good' results of modeling and fuzzy inference.

The detailed probabilistic fuzzy rules of the model and its parameters are constructed using empirical data, which contain information about the actual values of process variables. The data are used to create the weights of the model, i.e. the empirical probability distributions of fuzzy events. Rules with zero weights are eliminated from the model.

Due to the model's high complexity (which is the case for the model used to evaluate the effectiveness of logistics services), which contains a complete probability distribution in the weights of the rule (4), we propose to limit the number of rules to those with a proper level of support s. The support s of a rule is the probability of occurrence of all fuzzy events in the antecedent and consequent. In fact, the support of the first elementary rule in rule (4) results from the following equation:

$$\begin{aligned}
s(A_1^1, ..., A_1^N, B_{j/1}) &= P(A_1^1 \times ... \times A_1^N \times B_{j/1})\\
&= w_1 \cdot w_{j/1}.
\end{aligned} \tag{5}$$

The *prescriptive* approach to the construction of the analyzed knowledge base involves searching for such values of inference parameters and such value of minimum support of the rules for which we obtain an acceptable error level in the fit of the model to the empirical data, with a rule base that has the lowest complexity possible. The detailed algorithms for the construction of a probabilistic fuzzy knowledge base and model identification are given in [23, 27].

Inference with parametric family of t-norms

Having assumed an inference mechanism, we can obtain a quantitative result at the output of the system with a probabilistic fuzzy knowledge base. This inference is based on individual elementary rules, in accordance with the generalized *modus ponendo ponens* rule. Information on logical operations in an inference block can be found in [24, 25, 28]. In the literature, the non-elastic operators of triangular norms are most commonly used. We propose to use parametric triangular norms, which enable an easier optimization of inference parameters in order to improve the fit of inference results to empirical data. We employ Yager's parameterized tnorm:

$$\begin{aligned}
&\ddot{T}_Y\left(\{\mu_{A_i}(x_n)\}\,;\ddot{p}\right)\\
&= \begin{cases}
T_d(\{\mu_{A_i}(x_n)\}) \ \text{ for } \ \ddot{p} = 0,\\
MAX\left(0, 1 - \left(\sum\limits_{n=1}^{N} (1 - \mu_{A_i}(x_n))^{\ddot{p}}\right)^{1/\ddot{p}}\right)\\
\qquad\qquad\qquad\qquad \text{for } \ \ddot{p} \in (0, \infty),\\
T_m(\{\mu_{A_i}(x_n)\}) \ \text{ for } \ \ddot{p} = \infty
\end{cases}
\end{aligned} \tag{6}$$

where T_d – drastic t-norm, T_m – Zadeh's (minimum) t-norm, $\ddot{p}$ – shape factor of the t-norm operator, parameter $\ddot{p} \in \langle 0, \infty)$, that determines the type of the t-norm operator.

In the case of aggregation of antecedents, the parameterized t-norm was denoted with $\ddot{T}_{Y1}$, whereas in the case of implication, the corresponding operator was denoted with $\ddot{T}_{Y2}$. The shape factor parameters $\ddot{p}_1$, $\ddot{p}_2$ for the above operators are selected through optimization, with an assumed criterion of identification quality, e.g. the minimization of root-mean-square error (RMSE) for the training/testing data.

The procedure for the calculation of the quantitative result at the output of the inference system that evaluates the effectiveness of logistics services carried out in the model company follows the stages shown in Fig. 1. A detailed description of linguistic variables in the system is presented in the following section.

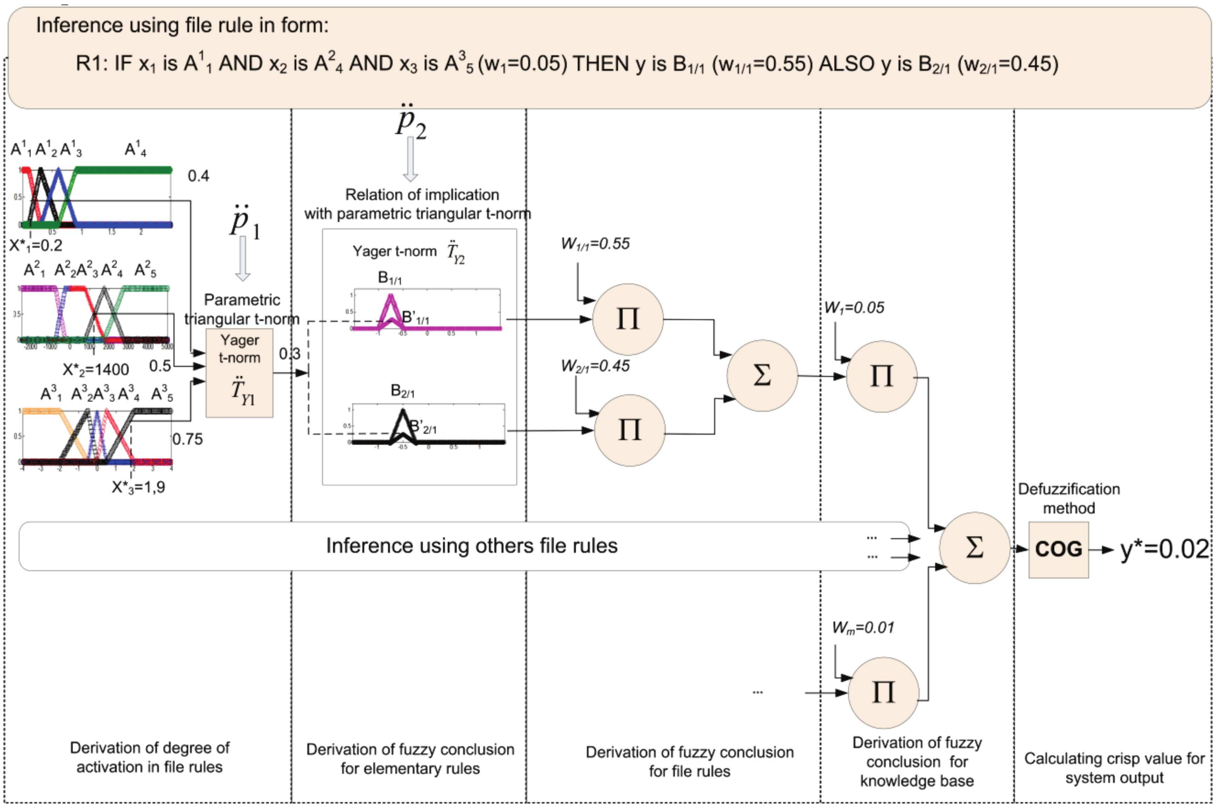

Fig. 1. Inference diagram based on a system with probabilistic fuzzy knowledge base for the evaluation of the effectiveness of logistics services (cf. [27]).

Illustrative example – case study: measuring and analysis of logistics services effectiveness

Below we demonstrate how the inference system with a probabilistic fuzzy knowledge base can be employed, using the example of measurement and analysis of the effectiveness of logistics services. The analysis pertains to a specific type of logistics services performed nationally and internationally in a model company of medium size logistics company TransSL.

The consistency between customer service and costs is essential to effectiveness. In the case of logistics services, effectiveness is not defined unambiguously – we lack precise methods of measuring effectiveness and evaluating such services. In any company, carrying out logistics services requires the evaluation of results of undertaken tasks with respect to their effectiveness. In this paper, effectiveness is not viewed in typical economic terms (as a relationship between costs and effects).

The effectiveness of logistics services is evaluated in two stages. For this purpose, a simplified set of indicators that are used to grade the service is specified as follows: income and profit (loss) from carrying out the logistics service, and the timely completion of work. Income represents the material value/benefit, resulting from carrying out the individual logistics services. Carrying out a given service incurs certain costs. The difference between income and the costs in total determines the level of profit or loss from a commission. To evaluate effectiveness, we assume another indicator, viz. the timely completion of a given service. A service can be performed ahead of the deadline, just in time, or after the deadline determined in the commission specifications. For the customer, the timely completion of a logistics service is a significant indicator.

The profitability indicator determined as:

$$\text{Profitability} = \frac{\text{Profit(Loss)}}{\text{Income}}, \tag{7}$$

constitutes a starting point for the evaluation of logistics services. Profitability determines the level of money-making for a given service, i.e. it is directly related to the level of costs of logistics services. Taking into account the profitability indicator and timely completion of work allows us to determine the effectiveness of a logistics service, both from the perspective of the customer and of the logistics service provider. A logistics service effectiveness indicator is determined based on the value of a profitability indicator, adjusted by the expert to include the indicator of timely completion of the service.

The basic unit for measuring the timeliness of a logistics service is a day (24 h). A positive value of this indicator signifies that the service was performed ahead of the deadline. A negative value signifies that the service was delayed. In such a case, the further from zero the value of the indicator, the more it affects the effectiveness of the logistics service in a negative way (decreasing profitability). It is assumed that the completion of work ahead of the deadline has less negative impact on the logistics service effectiveness indicator compared to untimely completion.

The logistics service effectiveness indicator defined above can be positive or negative. A negative value of the indicator signifies the ineffectiveness of performance of a given logistics service, whereas a positive value means that the service is performed effectively. The higher the value of the calculated indicator, the higher the effectiveness of services.

System assumptions

The structure of an inference system with a probabilistic fuzzy knowledge base is typical of a classical fuzzy system [29]. A specific representation of knowledge and a disparate inference mechanism, whose rules take into account the probability of appropriate fuzzy events during the calculations, are characteristic features of such a system. For a system measuring the effectiveness of logistics services, the input linguistic variables are: income, profit/loss and the timely completion of a logistics service. At the system output we obtain the effectiveness indicator taking into account two factors: the profitability and timeliness of a logistics service. The entire structure of the inference system is presented in Fig. 2.

For the purposes of creating the fuzzy system, the following linguistic representation of input and output variable is assumed:

L('LSincome')={'low', 'average', 'high', 'veryHigh'},

L('LSprofit')={'highNegative', 'lowNegative', 'lowPositive', 'averagePositive', 'highPositive'},

L('LStimelyCompletion')={'largeDelay', 'smallDelay', 'onTime', 'slightlyAheadOfDeadline', 'considerablyAheadOfDeadline'},

L('LSeffectiveness')={'veryHighIE', 'highIE', 'averageIE', 'lowIE', 'lowE', 'averageE', 'highE', 'veryHighE'},

where LS – logistics service, IE – ineffectiveness of a logistics service, E – effectiveness of a logistics service.

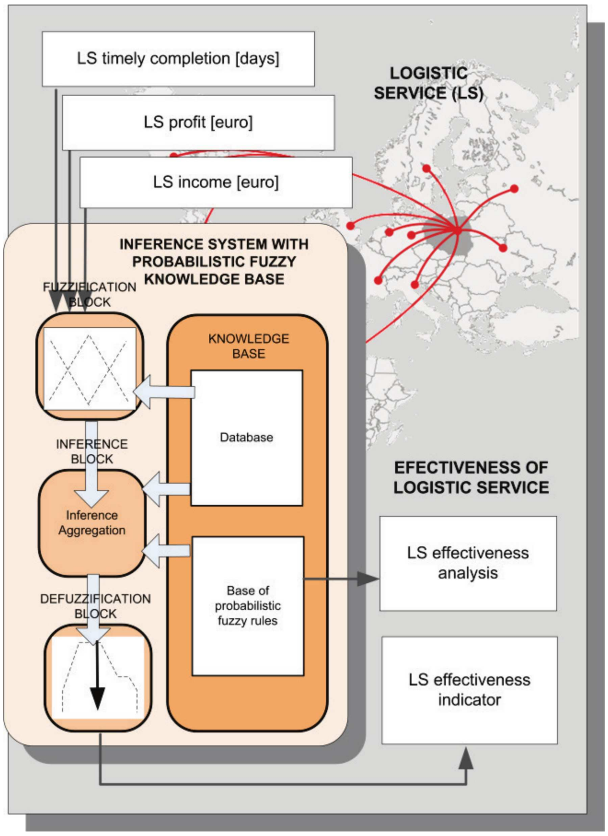

Fig. 2. Structure of inference system with probabilistic fuzzy knowledge base for the evaluation of the effectiveness of logistics service.

The detailed membership functions reflecting the mathematical relations for the linguistic values of the analyzed variables are presented in Fig. 3.

Due to a higher occurrence of positive evaluations for the profit indicator, the spread of linguistic values is not symmetric about zero. The above-mentioned values are often analyzed and discussed in the context of current business activity of companies, hence their linguistic terms result from casual information from experts (analysts, logistics service providers, etc.).

The linguistic description of variables along with the membership functions constitute the system database. A probabilistic fuzzy knowledge base is generated using empirical data – a set of indicator values and subjective effectiveness evaluations by experts for 257 logistics services performed over the specified time period in the TransSL company. A dataset containing evaluations of 50 logistics services is used for testing the system.

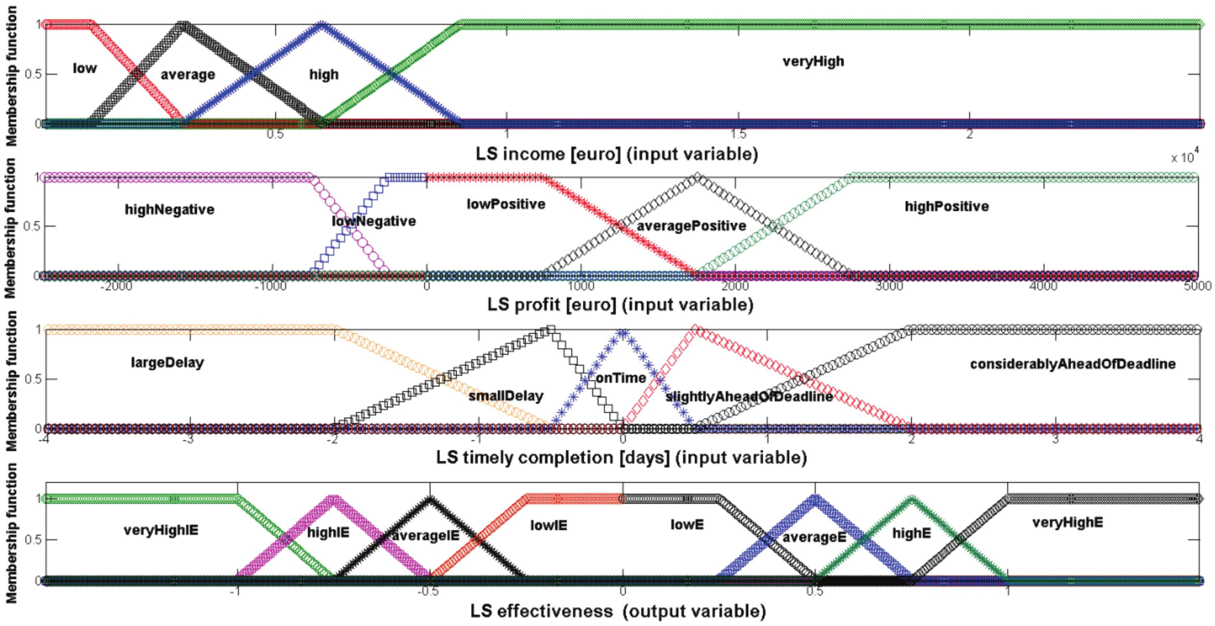

Fig. 3. Fuzzy sets for the system for evaluating the effectiveness of logistics services

Selection of system parameters

The use of the parameterized inference operator (6) facilitated parameter optimization during the application of the system to the evaluation of the effectiveness of logistics services. The minimization of the RMSE between the system output and empirical data is used as the criterion for assessing the quality of the fit. Sequential quadratic programming (SQP) is used as a method of optimizing the shape factor vector $[\ddot{p}_1, \ddot{p}_2]$ (vector of the shape factors for the inference operators $\ddot{T}_{Y1}$ and $\ddot{T}_{Y2}$) for the knowledge base of the system with a full probability distribution of fuzzy events in the rules. The training data analysis has shown that the optimum values of the shape factors are $\ddot{p}_1 = 999.999$, $\ddot{p}_2 = 0.97$. This gives an RMSE of 0.1582, and the knowledge base contains 239 elementary rules (70 file rules). An example of how the values of the shape factors for the inference operators $\ddot{T}_{Y1}$ and $\ddot{T}_{Y2}$ influence the quality of the fit for the analyzed application is shown in Fig. 4.

In order to make the knowledge base less complex, we increase the minimum value of the support of elementary rules *min s* (5) and eliminate the rules that do not comply with the condition of minimum support. This lead to a gradual worsening of the quality of the fit to the training data (cf. Fig. 5), and the quality of the fit to the testing data changed as well (cf. Fig. 6). Above a certain level (ca. 2.4×10^{-3}), the system outputs values averaged to such a degree that the error for testing data is level off. The diagrams reveal that the best result is obtained for the system with a support larger than 0.4×10^{-3}, where the error for the training data is lower (0.1563) and the number of elementary rules decreases to 166.

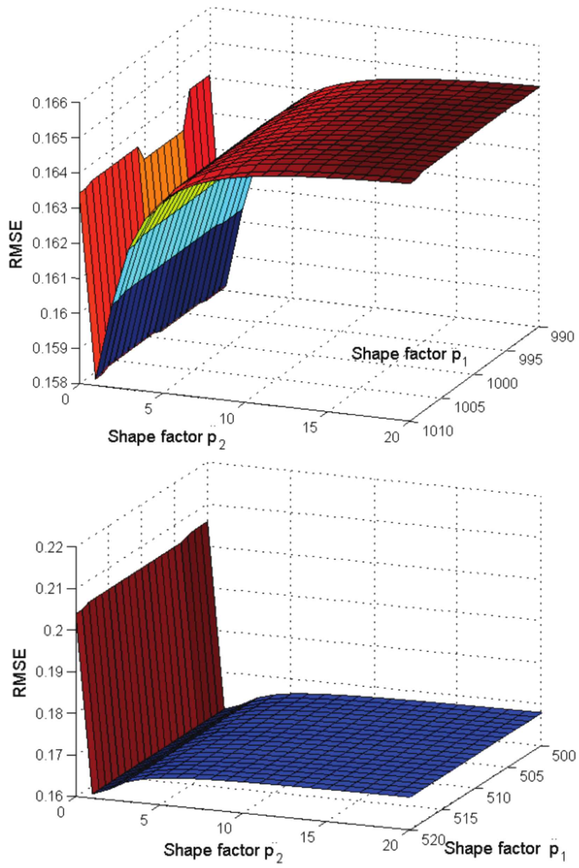

Fig. 4. Influence of shape factors of inference operators ($\ddot{T}_{Y1}$, $\ddot{T}_{Y2}$) on RMSE.

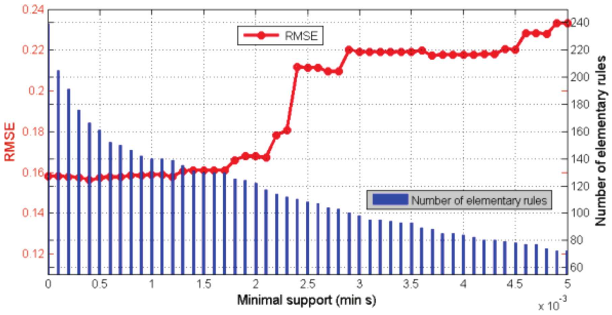

Fig. 5. Dependence of RMSE and knowledge base complexity on the minimum value of the rule support for training data.

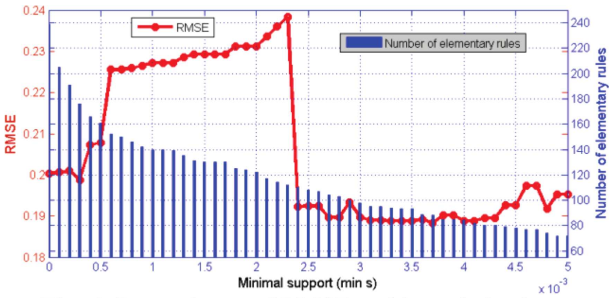

Fig. 6. Dependence of RMSE and knowledge base complexity on the minimum value of the rule support for testing data.

Results and discussion

The application of fuzzy inference in the proposed system allows to estimate the effectiveness of a logistics service based on income, profit and the timely completion of a service. The system does not give the exact results estimated by the experts, only approximate values, also in those ranges of indicators values, for which the company has not performed logistics services. Fig. 7 presents the dependences of the proposed (calculated) indicator of logistics service effectiveness on the selected evaluation factors. In the diagrams, an effectiveness of zero may signify that such an evaluation would never take place in reality (e.g. when profit exceeds income).

The analysis of the probabilistic fuzzy knowledge base allows to evaluate the effectiveness of logistics services performed by TransSL over a given time period. The most important file rules correspond to the most commonly occurring situations in the company. Below, we list only 4 most probable fuzzy rules:

R1: IF (LSincome IS veryHigh) AND (LSprofit IS highPositive) AND (LStimelyCompletion IS onTime) [0.0675] THEN (LSeffectiveness IS averageE) [0.4768]
ALSO (LSeffectiveness IS highE) [0.2536]
ALSO (LSeffectiveness IS lowE) [0.1629]
ALSO (LSeffectiveness IS veryHighE) [0.1067]

R2: IF (LSincome IS average) AND (LSprofit IS averagePositive) AND (LStimelyCompletion IS onTime) [0.0555] THEN (LSeffectiveness IS averageE) [0.4264]
ALSO (LSeffectiveness IS highE) [0.3840]
ALSO (LSeffectiveness IS lowE) [0.1221]
ALSO (LSeffectiveness IS veryHighE) [0.0675]

R3: IF (LSincome IS low) AND (LSprofit IS lowPositive) AND (LStimelyCompletion IS onTime) [0.0524] THEN (LSeffectiveness IS highE) [0.2981]
ALSO (LSeffectiveness IS lowE) [0.2918]
ALSO (LSeffectiveness IS averageE) [0.2751]
ALSO (LSeffectiveness IS veryHighE) [0.1350]

R4: IF (LSincome IS low) AND (LSprofit IS lowPositive) AND (LStimelyCompletion IS slightlyAheadOfDeadline) [0.0412] THEN (LSeffectiveness IS averageE) [0.4660]
ALSO (LSeffectiveness IS lowE) [0.3497]
ALSO (LSeffectiveness IS highE) [0.1550]
ALSO (LSeffectiveness IS veryHighE) [0.0293].

It can be inferred from the rules that the effectiveness of logistics services in TransSL is moderate. Usually, the services are performed on time or slightly ahead of the deadline, and the values of income vary (from very high to low), as do the values of profit, which is directly related to income. Rule no. 3 indicates that the effectiveness of logistics services with a relatively low income and low positive profit may be higher compared to services yielding high income. Other, less common rules indicate that high effectiveness can be achieved by performing logistics services with medium income and positive profit:

R11: IF (LSincome IS average) AND (LSprofit IS averagePositive) AND (LStimelyCompletion IS considerablyAheadOfDeadline) [0.0294] THEN (LSeffectiveness IS highE) [0.4059]
ALSO (LSeffectiveness IS averageE) [0.3118]
ALSO (LSeffectiveness IS lowE) [0.1818]
ALSO (LSeffectiveness IS veryHighE) [0.1005]

R14: IF (LSincome IS average) AND (LSprofit IS highPositive) AND (LStimelyCompletion IS onTime) [0.0262] THEN (LSeffectiveness IS highE) [0.6840]
ALSO (LSeffectiveness IS veryHighE) [0.1923]
ALSO (LSeffectiveness IS averageE) [0.1176]
ALSO (LSeffectiveness IS lowE) [0.0060]

R15: IF (LSincome IS average) AND (LSprofit IS averagePositive) AND (LStimelyCompletion IS slightlyAheadOfDeadline) [0.0250] THEN (LSeffectiveness IS highE) [0.4642]
ALSO (LSeffectiveness IS averageE) [0.3470]
ALSO (LSeffectiveness IS veryHighE) [0.1042]
ALSO (LSeffectiveness IS lowE) [0.0846].

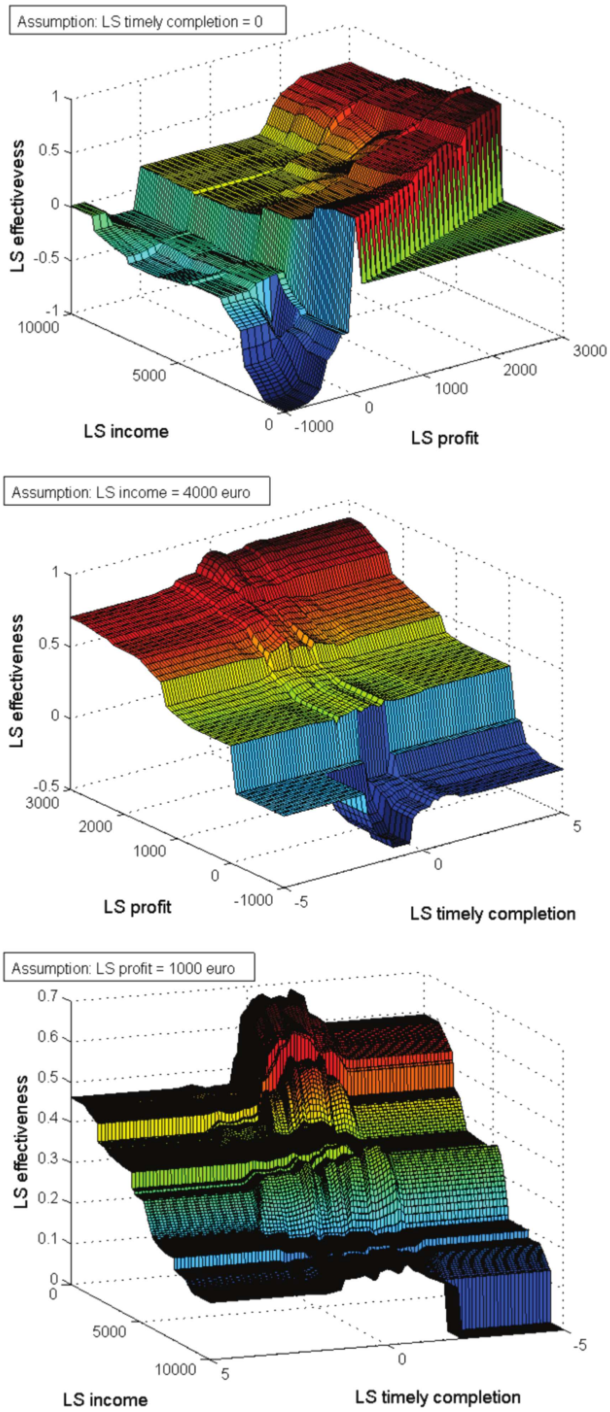

Fig. 7. Dependence of logistics service effectiveness on selected input indicators.

A very high effectiveness of logistics services is relatively rare in the company. According to empirical data a delay in the completion of services slightly affects the evaluation of TransSL business activity. In the knowledge base, we can find cases where a logistics service with a high or very high effectiveness is performed with a large delay or considerably ahead of the deadline. In economic practice, a company should satisfy customers' (or in this case employers') expectations to the highest degree. In particular, this pertains to the completion of the entire range of entrusted tasks, quality of provided services, as well as meeting the deadline and the agreed level of service price. A delay in carrying out a logistics service can result in additional penalties and/or the cessation of commissions from the customer, to whom a logistics service was not provided on time.

Conclusions

We presented a computationally efficient, qualitative-quantitative method of measurement and evaluation of the effectiveness of logistics services in a logistics company. The application of a system with a probabilistic fuzzy knowledge base allows to express the uncertainty as the probabilities of effectiveness indicators, specified in linguistic terms. Such an approach to the problem allows to create a rule base based on empirical data and data gathered from experts. Using knowledge from several experts to determine the shape of the membership functions influence the evaluation in the context of generalized, objective criteria. The proposed probabilistic fuzzy model of knowledge is easy to interpretation by humans. This constitutes a significant advantage when strategic decisions concerning logistics services are made. The proposed system can be further developed by expanding the set of evaluation indicators.

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